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A Quasi-experimental Approach

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Abstract

We test whether firms react to changes in the wages and size of their competitors. We use a unique institutional feature of public procurement auctions in Brazil: the moment in which the auction ends is random. For close auctions, winner and runner-up are as good as randomly assigned. We first show that firm-specific demand shocks lead to increases in the size and wages of the firm receiving the shock. Then, we document that these firm-specific demand shocks lead to increased wages of other (competing) firms in the same local labor market. We do not find negative effects on competitors' firm size. The effects are driven by competing firms responding to demand shocks from firms with high labor market share.

JEL classifications: J01, J23, J30
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1 Introduction

Do firms react strategically to wages and employment set by their competitors? The answer to this question is central to understanding wage and employment determination in the labor market, and in particular the transmission of changes in firm-specific demand or productivity to the rest of the market. Although this question is at the heart of labor economics, little progress has been made due to the difficulty of finding plausibly exogenous shifts in a firm's size or wage that are unrelated to the determinants of the size and wages of its competitors.

Strategic interaction is a natural implication of market power due to market concentration. There is now evidence in a variety of contexts and countries that increased market concentration is associated with lower wages (Arnold, 2019; Azar et al., 2020; Felix, 2021; Benmelech et al., 2022; Azar et al., 2022; Schubert et al., 2024; Guanziroli, 2022; Cali and Presidente, 2023; Azkarate-Askasua and Zerecero, 2023) and that larger firms are associated with higher wage markdown (Amodio and De Roux, 2024; Yeh et al., 2022; Amodio et al., 2022).[1] An implication of market power due to market concentration is that firms react to the decisions of their competitors (Bhaskar et al., 2002; Berger et al., 2022, 2023). In particular, if one firm (exogenously) grows or increases its wage, all other firms in the labor market can react in terms of wage and employment size as a response. However, there is very little evidence on whether and how firms respond to their competitors. The empirical challenge is clear. It is very difficult to identify a firm-specific shock at the firm level, completely unrelated to other direct market effects on their competitors.

In this paper, we leverage quasi-experimental variation from procurement auctions where the winning firm sells goods to the government. A unique feature in these auctions generates randomness in the identity of the contract winner. We then test how wages and employment of firms within the same local labor market react to a (size and wage increasing) demand shock on a competitor.

To do so, we obtained information on the universe of public procurement auctions conducted by the Brazilian federal government. We have scraped the official government website containing millions of HTML records of these auctions and transformed them into usable data. In these auctions, firms repeatedly bid for a contract with the government, and all participants always observe the current winning (lowest) bid. The final (lowest) bid is the price the winning firm gets to sell to the government (descending first price auction).

[1] Amodio et al. (2024) show that the positive relationship between firm size and wage markdown is present for a variety of countries across the world using harmonized micro data covering 83 low and middle-income countries.

Unlike other settings, these auctions have a unique feature: the moment at which the auction ends is random (chosen by a computer and unknown to participants). In particular, the duration of each auction comes from a uniform distribution that is independent of any firm or auction characteristic and bidding behavior within the auction. Furthermore, they include products from all industries, from cleaning supplies to vehicle parts, medical equipment, and computers. We merged these data with employer-employee matched data for the universe of formal workers in Brazil, *Relação Anual de Informações Sociais* (RAIS). In these data, we observe both firm and worker characteristics, such as the start and end of employment, earnings, contractual wages, education, occupation, gender, and industry.

The random ending of the auction provides us with a natural experiment. For auctions in which two firms are constantly outbidding each other incrementally, the winner and runner-up are as good as randomly assigned (Ferraz et al., 2015; Carvalho et al., 2023). For the entirety of the paper, we focus on close auctions—which we define to be when the two lowest bids are within 0.5% difference in value and placed in the final 30 seconds of the auction. Intuitively, consider two firms, A and B, constantly outbidding each other by a few cents and placing their bids seconds apart. The random ending implies that the auction might end when either firm A or firm B is the lowest bidder. Then, both firms are in expectation similar in predetermined characteristics. As a result, we can use the runner-up as a natural counterfactual for the treated (winning) firm and credibly estimate the effect of firm-level demand shocks on the remaining firms in their same local labor market.

Carvalho et al. (2023) show that firms winning one of these close auctions increase their wages and number of employees for up to 4 years relative to the runner-up. A natural following question, therefore, is how other firms in the same labor market respond to this movement.

We use two theoretical frameworks to guide our empirical analysis and to think about the mechanisms underlying our empirical findings. We do not take a stand on any of the models since the competitor's response depends on the specific underlying market conduct. For example, firms can interact via search and matching with bargaining. Alternatively, they can compete for workers in an oligopsonistic way in which they may set wages via Bertrand, Cournout, Stackelberg, or some other way. Instead, we use the models to illustrate how firms are expected to react to changes in employment and wages of their competitors in concentrated labor markets.

The first setting we consider is one where granular firms compete (*a la* Cournot) against each other and internalize the fact that they each face an upward-sloping labor supply curve (Berger et al., 2022). The firm receiving the (size increasing) demand shock raises its wage, attracting a larger workforce and increasing its size. Using this theoretical framework, we formally characterize the response of the size and wage of a competitor firm. Due to Cournot competition, employment levels are strategic substitutes across firms. Competitors are expected to decrease their size as a response. The magnitude of this negative response is expected to increase with the labor market share of the competitor in question and decrease in labor market share of the firm receiving the (size increasing) demand shock. Generally, the wage response of competitor firms is ambiguous. However, for a low enough labor market share of the firm receiving the (size increasing) demand shock, competitors are expected to increase their wages. We test these predictions using our quasi-experimental variation.

The second setting is one of search and matching with bargaining under the presence of granular firms (Jarosch et al., 2024). In this context, granular firms commit to not re-hiring a worker if bargaining breaks down. This corresponds to firms taking out their own job posting from their workers' outside option, allowing the firm to pay workers lower wages. The larger the share of the firm in the local labor market, the larger the markdown on wages due to this channel.

Under this setting, if a granular firm j increases its wage, a competitor firm i must increase its wages to keep its workers, leading to a higher bargained wage. This effect increases with the size of the granular firm j. In contrast, increases in wages by atomistic (approximately zero labor market share) firms have no impact on the wage paid by firm i. This effect of wages of a granular firm j in wages of firm i is also increasing in the labor market share of firm i. Intuitively, because firms commit to not hiring the worker if bargaining breaks down, the larger a firm i is, the longer the worker stays unemployed if negotiations with firm i break down. This, in turn, makes the wage received by any granular competing firm j all the more important for the worker's utility under a breakdown in negotiations (worker's outside option).

In our empirical analysis, we start by documenting the employment and wage effects on auction winners. We find that being the lowest bidder causes the firm to have more employees and higher wages for at least two years thereafter.

Next, we define the local labor market as a municipality-industry-year cell. Then, for each close auction, we follow all firms in the same local labor market of the winner and runner-up. We find that winning a close auction leads to 0.15%, 0.18%, and 0.23% higher wages at the year of the auction, one year and two years later, respectively, for competing firms in the same local labor markets. We do not find negative effects on competitors' firm size. Taken together with the effect on lowest bidder size and wage, these estimates imply that for every 1% increase in wages by the lowest bidder, wages increase by 0.17% for competitors at the moment of the auction, by 0.13% one year later, and by 0.14% two years later. Consistent with models of firm strategic interactions, we find these wage effects are driven by auction participants with above-median labor market share. In particular, the lowest bidder, which has a labor market share above the median, causes their competitors to raise wages by 0.26%, 0.37%, and 0.48%, at the year of the auction, one year later, and two years later, respectively. We also redo our analysis after dropping observations from local labor markets with more than 500 firms (where strategic interaction might be less likely). Our results remain qualitatively similar.

We next ask to what extent firms compete in the same occupation market. We then consider the local labor market as municipality-occupation-year cell. The unit of observation in the analysis becomes a firm-occupation. Since the number of observations explodes for some markets, we restrict our analysis to local labor markets with less than 500 firm-occupation observations. While we find that on average firms do not respond in size or wages to being in the same occupation-municipality-year as the lowest bidder, this masks substantial heterogeneity. When focusing on competitors of high labor market share firms, we find that competitor wages increase by 0.32%, 0.5%, and 0.48% higher wages at the moment of the auction, one year later, and two years later, respectively.

Our paper relates to the growing literature documenting empirically a negative relationship between market concentration and wages, consistent with market concentration leading to labor market power. The negative correlation between market concentration and wages is well documented (Azar et al. (2022) and Azar et al. (2020)), and it is robust to using within-occupation variation (Schubert et al., 2024) and to being instrumented by merger activity (Benmelech et al., 2022). There is also evidence that market concentration is negatively correlated with hiring (Marinescu et al., 2021) and has implications for worker composition and firm survival (Dodini et al., 2022).

Second, our paper relates to a recent literature analyzing how a firm's share of the labor market impacts its wage and employment. Importantly, all else equal, firms with larger labor market share pay lower wages, irrespective of whether wages are set via wage bargaining (Jarosch et al., 2024) or wage posting (Berger et al., 2022; Azkarate-Askasua and Zerecero, 2023). Recent papers have studied this relationship empirically by using mass layoffs of competitors as shifts in a firm's labor market share (Azkarate-Askasua and Zerecero, 2023).

Third, our findings relate to a recent literature analyzing the effect of mergers on the wages paid to different types of workers in the firm (Lagaras, 2019; Thoresson, 2021; Prager and Schmitt, 2021; Guanziroli, 2022), and the effect of mergers on the wages paid in competing firms (Arnold, 2019; Guanziroli, 2022). While Arnold (2019) find that merger-induced market concentration is associated with lower wages in the local labor market, he also documents a positive correlation between concentration and market-level employment. Guanziroli (2022) find that a retail pharmacy merger led to lower wages and a statistically insignificant decrease in employment among merging firms while leading to lower wages and higher employment among competing firms.

While these three strands of literature have focused on how changes to market-level concentration or a firm's specific labor market share affect wages and employment at the firm or market level, we focus, instead, on verifying how a (size-increasing) demand shock to a firm affects its competitors. In doing so, we test not the effect of changes in market concentration (which is in itself an endogenous equilibrium result of firm decisions) but rather a natural implication of market power driven by market concentration: strategic wage and employment setting by firms. Furthermore, we quantify the response elasticity of a firm with respect to changes in wage and employment of its competitor.

Finally, our findings contribute to the literature analyzing the response of competitors to changes in wage or employment of a firm in the same local labor market. The literature has focused on particular case studies, such as a legislated change in nurse wages at Department of Veterans Affairs Hospitals (Staiger et al., 2010) or observed increases in company-wide wage floors in large retailers, observing 20 such events for 5 large retailers (Derenoncourt and Weil, 2024). As discussed in Derenoncourt and Weil (2024), the underlying motivations for these company-wide wage floor increases may be multi-faceted, potentially capturing responses to higher unionization attempts, adjustments induced by anticipated increased statutory minimum wages, or endogenous decisions to attract and retain more workers.[2] We contribute to this literature by using hundreds of thousands of close auctions, each interpreted as an experiment in itself, due to their random ending, including products from all industries, as drivers of increases in firm-specific wage and employment. Our finding that for every 1% increase in wages by the lowest bidder, competitors increase their wages by 0.17% is close to the cross-hospital wage elasticity found by Staiger et al. (2010) of 0.19%.

[2]See the penultimate paragraph in Section 2 of Derenoncourt and Weil (2024).

2 Theoretical Frameworks

In this section, we derive the expressions for the firm response to an increase in employment size and wages of a competitor. We consider two separate theoretical frameworks, both of which have implications for how competitors react to a change in employment size or wage of a given firm in the local labor market.

2.1 Berger et al. (2022)

The first framework we consider is that of Berger et al. (2022), in which firms compete by choosing their optimal size given the size chosen by their competitors. The economy is composed of a continuum of local labor markets $j \in [0,1]$, each with an exogenous and finite number of firms. Since the equilibrium concept is Cournot, firms maximize profits by taking the actions of competitors as given. Firm i in market j in period t chooses capital, k_{ijt}, and employment size, n_{ijt}, to maximize

$$\max_{k_{ijt}, n_{ijt}} z_{ijt}(k_{ijt}^{1-\gamma} n_{ijt}^{\gamma})^{\alpha} - R_t k_{ijt} - w(n_{ijt}, n^*_{-ijt}, N_t, W_t) n_{ijt} \tag{1}$$

where R_t is the cost of renting capital and n^*_{-ijt} represents the size chosen by all other firms other than i. The maximization is done subject to the upward labor supply faced by the firm

$$w = \left(\frac{n_{ijt}}{n_{jt}(n_{ijt}, n_{-ijt})}\right)^{\frac{1}{\eta}} \left(\frac{n_{jt}(n_{ijt}, n^*_{-ijt})}{N_t}\right)^{\frac{1}{\theta}} W_t \tag{2}$$

where n_{jt} is a market j level index,

$$n_{jt}(n_{ijt}, n^*_{-ijt}) = [n_{ijt}^{\frac{\eta+1}{\eta}} + \sum_{k \neq i} n_{kjt}^{\frac{\eta+1}{\eta}}]^{\frac{\eta}{\eta+1}} \tag{3}$$

and N_t, W_t are aggregate economy-level indexes. The term η captures the cost of moving labor across firms within market, while θ captures the cost of moving labor across markets. In order to have market power at the local labor market level, we need $\eta > \theta$. See Berger et al. (2022) for details in the derivation of the labor supply curve.

Let us first characterize the optimal choice of n_{ijt} for firm i at market j given everything else. The first order condition for n_{ijt} is given by

$$\alpha\gamma \frac{y_{ijt}}{n_{ijt}} = w_{ijt}\left[\frac{\partial w_{ijt}}{\partial n_{ijt}} \frac{n_{ijt}}{w_{ijt}} + 1\right]. \tag{4}$$

Now note that

$$\frac{\partial w_{ijt}}{\partial n_{ijt}} = \frac{w_{ijt}}{n_{ijt}}[\frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})\frac{\partial n_{jt}}{\partial n_{ijt}}] \quad \text{and} \quad \frac{\partial n_{jt}}{\partial n_{ijt}} = (\frac{n_{ijt}}{n_{jt}})^{\frac{1+\eta}{\eta}}, \tag{5}$$

and so,

$$\alpha\gamma\frac{y_{ijt}}{n_{ijt}} = w_{ijt}[\frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}} + 1]. \tag{6}$$

The above equation completely characterizes the choice of optimal n_{ijt}. Note also that the expression for the elasticity of labor supply is

$$\frac{\partial w_{ijt}}{\partial n_{ijt}}\frac{n_{ijt}}{w_{ijt}} = \frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}} = \frac{1}{\eta} + (\frac{\eta - \theta}{\theta\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}} > 0, \text{since } \eta > \theta. \tag{7}$$

From the expression above we see how the elasticity of labor supply faced by a firm depends on exogenous parameters θ and η and an endogenous object, the labor share of the firm $\frac{n_{ijt}}{n_t}$.

Using this expression we can totally differentiate with respect to n_{ijt} and n_{kjt} to obtain Proposition 1 below.

Proposition 1.

$$\frac{dn_{ijt}}{dn_{kjt}} = \frac{-w_{ijt}(\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}\frac{1+\eta}{\eta}[\frac{1}{n_{ijt}} - \frac{1}{n_t}(\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}}] - \frac{w_{ijt}}{n_{ijt}}(\frac{1}{\theta} - \frac{1}{\eta})^2(\frac{n_{ijt}}{n_t})^{\frac{2(1+\eta)}{\eta}}}{\alpha\gamma(1-\alpha\gamma)z_{ijt}k_{ijt}^{\alpha(1-\gamma)}n_{ijt}^{\alpha\gamma-2} + B(B+1) + w_{ijt}(\frac{1}{\theta} - \frac{1}{\eta})(\frac{1+\eta}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1}{\eta}}A} < 0 \tag{8}$$

where

$$B \equiv (\frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}) > 0. \tag{9}$$

and

$$A = (\frac{n_t^{1+\frac{1+\eta}{\eta}} - n_{ijt}^{1+\frac{1+\eta}{\eta}}}{n_t^2 n_t^{\frac{1+\eta}{\eta}}}) > 0. \tag{10}$$

The sign of the derivative comes from the fact that

$$\eta > \theta \Rightarrow \frac{1}{\theta} - \frac{1}{\eta} > 0 \tag{11}$$

and by definition since $n_t > n_{ijt}$, $n_t > n_{kjt}$ for all j, k, then,

$$\frac{1}{n_{ijt}} - \frac{1}{n_t}(\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}} > 0. \tag{12}$$

It follows that employment of a firm j unambiguously decreases with employment of a competing firm k. Some properties of this response include the following:

- For firms with very low labor market share $\frac{n_{ijt}}{n_t} \approx 0$ we get $\frac{dn_{ijt}}{dn_{kjt}} \approx 0$.
- When the firm k receiving the shock has a higher labor market share, high $\frac{n_{kjt}}{n_t}$, the effect is smaller because the magnitude of $\frac{1}{n_{ijt}} - \frac{1}{n_t}(\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}}$ decreases.

Next, we might wonder how does the wage of firm j respond to an increase in the size of firm k. Proposition 2 characterizes the response.

Proposition 2.

$$\frac{dw_{ijt}}{dn_{kjt}} = \frac{1}{\eta}\frac{w_{ijt}}{n_{ijt}}\frac{dn_{ijt}}{dn_{kjt}} + (\frac{1}{\theta} - \frac{1}{\eta})\frac{w_{ijt}}{N_t}[\frac{dn_{ijt}}{dn_{kjt}}(\frac{n_{ijt}}{n_{jt}})^{\frac{1}{\eta}} + (\frac{n_{kjt}}{n_{jt}})^{\frac{1}{\eta}}], \tag{13}$$

and

$$\lim_{(\frac{n_{kjt}}{n_{jt}}) \to 0} \frac{dw_{ijt}}{dn_{kjt}} < 0. \tag{14}$$

From Proposition 2 see that

$$\frac{dn_{ijt}}{dn_{kjt}}(\frac{n_{ijt}}{n_{jt}})^{\frac{1}{\eta}} + (\frac{n_{kjt}}{n_{jt}})^{\frac{1}{\eta}} < 0 \Rightarrow -dn_{ijt}(\frac{n_{ijt}}{n_{jt}})^{\frac{1}{\eta}} > dn_{kjt}(\frac{n_{kjt}}{n_{jt}})^{\frac{1}{\eta}} \Rightarrow \frac{dw_{ijt}}{dn_{kjt}} < 0. \tag{15}$$

Intuitively, the sign of the derivative depends on the decrease in size of the competitor firm, dn_{ijt}, relative to the size increase in the firm receiving the demand shock, dn_{ijt}, weighted by their importance in the market, their labor market share. If the labor share weighted decrease in the size of the competitor i is larger than that of the increase in size of firm k, then, firm i decreases its wages. From the expression for $\frac{dw_{ijt}}{dn_{kjt}}$, we also see that when the firm receiving the shock has a very small labor share, $\frac{n_{kjt}}{n_{jt}} \approx 0$, then, the last term is close to zero and the derivative is negative.

In this framework, the only possibility for firms to not respond with their size is if their labor market share is sufficiently small, $\frac{n_{ijt}}{n_t} \approx 0$. In this case the expression for $\frac{dw_{ijt}}{dn_{kjt}}$ simplifies to

$$\frac{dw_{ijt}}{dn_{kjt}} = (\frac{1}{\theta} - \frac{1}{\eta})\frac{w_{ijt}}{N_t}(\frac{n_{kjt}}{n_{jt}})^{\frac{1}{\eta}} > 0. \tag{16}$$

In other words, firms with small labor market share respond to an increase in size by a competitor via wage increases without any change in firm size.

2.2 Jarosch et al. (2024)

The second framework we consider is a continuous time version of the search and matching framework with bargaining under granular firms proposed by Jarosch et al. (2024).[3] Different than bargaining under atomistic firms, granular firms commit to not hiring a worker if bargaining breaks down. In other words, firms take out their own job posting from their workers' outside option, allowing them to pay lower wages. The larger the firm in the market, the larger the markdown in wages due to this channel.

The economy is composed of a finite number of firms i each with size f_i in the labor market. Following the authors, we consider f_i is also the probability an unemployed worker matches with firm i. Let r denote the parameter controlling the discounting of the household. Let λ be the rate at which an unemployed worker meets a firm and b the income while unemployed. The value function of an unemployed worker, U, is given by

$$rU = b + \lambda \sum_{i} f_j (W_j - U) \tag{17}$$

where W_i is the value function associated to working for firm i. Let w_i denote wage paid by firm i and δ the exogenous probability the match is destroyed, then,

$$rW_i = w_i + \delta(U - W_i). \tag{18}$$

Wages are determined by Nash Bargaining. When bargaining with firm i, a worker takes into account that if negotiations break down, she will no longer be able to work for firm i until she finds another job first.[4] As a result, the outside option U_i used by the worker when bargaining with firm i is given by

$$rU_i = b + \lambda \sum_{j \neq i} f_j (W_j - U_i). \tag{19}$$

Let J_i and V_i be the usual value functions for a filled vacancy and unfilled vacancy, respectively (see Appendix for details). As a result, wages are determined by

$$\beta(J_i - V_i) = (1 - \beta)(W_i - U_i). \tag{20}$$

[3]We consider a continuous time version to make the algebra cleaner. All derivations are unchanged if we consider discrete time.

[4]Following the authors, we consider that the punishment by a firm for a negotiation breakdown lasts until the worker finds a job with a competitor.

We consider, as in Jarosch et al. (2024), that the free condition holds, $V_i = 0$. As a result, the bargaining equation above is simplified to

$$\beta(\frac{y_i - w_i}{r+\delta}) = (1-\beta)(\frac{w_i + \delta U}{r+\delta} - U_i) \tag{21}$$

which implies wages are characterized by

$$w_i = \beta y_i + r(1-\beta)U_i + (1-\beta)\delta(U_i - U). \tag{22}$$

Proposition 3. *Holding fixed the size of firm i in the market f_i we obtain the following*

$$\frac{\partial w_i}{\partial w_j} = \frac{\lambda f_j}{(r+\delta)(r+\delta(1-f_i))} + \frac{\delta\lambda^2(1-f_i)f_j}{r(r+\delta)(r+\delta+\lambda)(r+\lambda(1-f_i))} > 0, \tag{23}$$

$$\frac{\partial w_i^2}{\partial w_j \partial f_j} > 0 \quad and \quad f_j = 0 \Rightarrow \frac{\partial w_i}{\partial w_j} = 0, \tag{24}$$

$$\frac{\partial w_i^2}{\partial w_j \partial f_i} = \frac{\delta\lambda f_j}{(r+\delta+\lambda)(r+\delta(1-f_i))^2} > 0, \tag{25}$$

and

$$\frac{\partial w_i}{\partial f_j} = \frac{\lambda w_j}{(r+\delta)(r+\delta(1-f_i))} + \frac{\delta\lambda^2(1-f_i)w_j}{r(r+\delta)(r+\delta+\lambda)(r+\lambda(1-f_i))} > 0. \tag{26}$$

The proposition above tells us that the wage of a given firm i is increasing in the wage of an arbitrary competitor j. Intuitively, the more a competitor firm j pays, the more firm i needs to pay to keep the worker. This effect is no longer present if the competitor j in question is atomistic ($f_j \approx 0$) since, in this case, the average wage the worker can get in firms other than i is unchanged. Conversely, the increase in wage by i is even larger if j increases both their wage w_j and their size f_j. A rise in f_j directly leads to higher w_i and increases the response of w_i to w_j. Finally, note that the response of w_i to w_j is stronger the larger is firm i. The larger the size of firm i, the longer the worker would stay unemployed if they decided to walk away from their job, making any wage received by a competing firm j even more important in their threat to leave firm i.

Of course, the total response of wages of firm i depends on the relative changes in f_i and f_j following the increase in w_i. In any case, the proposition above shows us that, even if the size of firm i does not change following the increase in w_j, its wage should.

Importantly, firm i increases its wage w_i even if they are atomistic ($f_i \approx 0$). Hence, even in the extreme case where the increase in size and wage by firm j pushes firm i to $f_i = 0$, the prediction that wages of firm i increases still holds,

$$f_i = 0 \Rightarrow \frac{\partial w_i}{\partial w_j} = \frac{\lambda f_j}{(r+\delta)^2} + \frac{\delta \lambda^2 f_j}{r(r+\delta)(r+\delta+\lambda)(r+\lambda)} > 0. \tag{27}$$

2.3 Summary

We have gone over two theories of granular firms in imperfect labor markets. These theoretical frameworks suggest that firms can react to higher wages and size of their competitor by changing their wages and/or changing their size. Importantly, these responses depend on the labor market share of both the reacting firm and the firm that received the shock. In what follows, we test the presence of such strategic interaction in the data.

3 Data

We combine two large administrative data sets: matched employer-employee data from Relação Anual de Informações Sociais (RAIS) and online procurement auctions conducted by the government of Brazil in the ComprasNet platform. ComprasNet is the online environment where the government conducts its auctions, and where the auction records are stored.

3.1 Auctions Background and Data

In this section, we explain the features of the auctions in our data. The governmental branch interested in procuring goods publishes an announcement of the auction, specifying the product and quantity being procured, the date and time when the auction will be conducted, which documents should be provided by the winning firm, and the location and date where the goods should be delivered. In the data, there are 3,264 purchasing governmental branches, which are relatively disaggregated governmental levels. These can be, for example, an Army battalion, a university, or a hospital. After this announcement, interested firms submit a sealed bid before the time of the auction. When the auction begins, the sealed bids are revealed to all participants and firms may start placing new bids in a descending price auction. To do so, a bidder needs to type the bid value in the auction page.

At each moment, all firms observe the currently winning bid. The winner is the firm that has placed the lowest bid when the auction ends. The auction has two parts: there is a first phase when the auction cannot end, and a final, random phase that can end at any moment—and after which no more bids are accepted. After some time elapsed in the first phase, the auctioneer announces when the final, random phase of the auction will begin. The duration of the first phase is at the auctioneer's discretion. The final phase has a random duration between 0 and 30 minutes, drawn electronically by the platform from a uniform distribution.

No participant or auctioneer can interfere with the duration of the random phase or know it before the auction ends. When the random phase ends, no new bids are accepted, and the firm that has placed the lowest bid at that moment has the chance of selling the procured good to the governmental branch. The auctioneer messages the lowest bidder and asks that it send the required documentation, setting a deadline for this. This deadline is usually within a few hours after the random phase ends. If the lowest bidding firm does not send the documentation in time, the auctioneer eliminates this participant and asks the second-placed firm to send it. This continues until a firm successfully sends the required documents or until all participants have been called. A firm that successfully sends the required documents wins the contract to sell the procured goods. If all firms are called and none can produce all the needed documents, the auction is canceled.

Each auction is automatically registered by the ComprasNet platform in an auction record, which contains detailed specifications and quantity of the products being procured, the government's reference price, the tax identification number (CNPJ) of each participating firm, all bids placed and their respective timestamps, the contract winner, and contract value. It also contains the timestamps of crucial moments in the auction, particularly the start and ending of the random phase. We have scraped each auction record from the government's website and complemented it with detailed product classification codes.[5] We process millions of auction reports into a data set with all 9.2 million ComprasNet online auctions conducted between 2011 and 2016. Auctions are not concentrated in any specific group of products (see Appendix Table A1 for a breakdown).[6]

3.2 Employer-Employee Data

Our labor market data come from RAIS (Relação Anual de Informações Sociais), which contains the universe of formal jobs in Brazil. We take observations from 2009-2018 and merge them with the auctions data using the firm's tax identification number (Cadastro

[5] A 6-digit product code based on the Federal Supply Classification (FSC), developed by the United States' Office of the Secretary of Defense. `https://mn.gov/admin/assets/DISP_h2book[1]_tcm36-281917.pdf`.

[6] See Carvalho et al. (2023) for further detailed description of the data construction.

Nacional de Pessoa Jurídica, CNPJ). In RAIS, for each job we observe a unique worker identifier, contractual wage, hours, earnings, race, sex, age, schooling, occupation, hiring and separation dates. For each firm, we observe its CNPJ, the municipality where it is located and its industry. The level of observation in RAIS is a job, so to build an annual data set we take only jobs that existed at the end of each year.

For our identification strategy, which is explained in detail in Section 4, we focus only on close auctions where it is reasonable to assume that the lowest and second lowest bidders are as good as randomly assigned. After imposing this restriction and merging the two data sets, we are left with approximately 200,000 close auctions with two firms in each, the lowest and second lowest bidder.

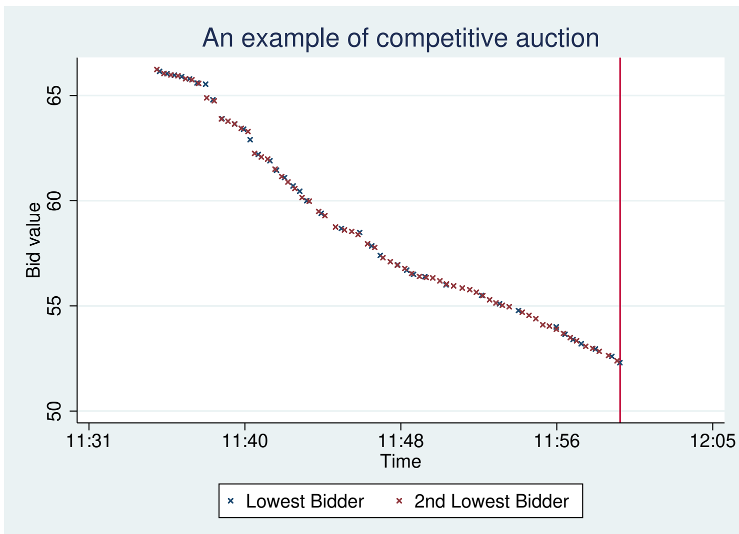
4 Empirical Design

In this section, we establish how we use a unique feature of Brazilian procurement auctions to obtain credible quasi-experimental variation in firm-specific demand shocks. Our main goal is to estimate the effect of demand shocks on firm wages and number of employees and, subsequently, on its competitors' response. Clearly, simply comparing auction winners and losers raises several concerns. These firms are likely different in their production function, size, and worker composition, any of which could affect wages and be correlated with winning an auction.

To overcome these endogeneity concerns, we use close auctions, relying on the practical frictions generated by the random ending and the manual time-consuming process for a firm to outbid a current winning bid. Figure 1 shows an example of a close auction. We plot the bid values of two competing firms: the first and the second placed bidder by the end of the auction. As time elapses, each firm observes the lowest bid at the moment and decides whether to place a new bid. If it does, the firm must enter the bid manually on the auction page, which requires at least a few seconds. In the figure, we see how firms keep outbidding one another by incremental amounts until the end of the auction displayed by the vertical line. At this point, the lowest bidder wins the auction. Because the time the auction ends is not known, this creates randomness in the identity of the lowest bidder in close auctions. Had the auction ended a few seconds earlier or lasted a few seconds longer, the two lowest bidding firms would be switched. Since we observe each bid value and bid timestamp for each auction, we are able to verify that indeed the lowest bidder and runner-up identities switch if the auction had ended a few seconds earlier (see Appendix Table A2). We also exclude auctions in which a firm has participated in more than two thousand close auctions during the 2011-2016 period.[7]

We use the time and value of each bid for all auctions and firms in our full data set to formulate our empirical definition of close auctions. We define these as auctions having at least two bids in the last 30 seconds and with a difference between bid values of at most 0.5%. After defining these auctions, we keep the firm that placed the lowest bid and the firm that placed the second lowest bid. By doing this, we ensure that we are, on average, looking at ex-ante identical firms.

Figure 1: Example of Close Auction



We interpret each close auction as an experiment in itself. So for each auction, we follow all firms from the same local labor market of the lowest bidder and runner-up, and compare their main outcomes. We use job-level information from RAIS to construct firm-level earnings and worker composition variables for periods before and after the auction date. Our analysis uses annual earnings and firm size as the main outcomes.

Our empirical design does not require any knowledge or assumption about the strategies of the firm. We are relying only on the practical frictions generated by the manual time-consuming insertion of the bid and the randomness of the auction end.[8] When the

[7]We do this because firms that participate excessively end up being treatment and control units with high and similar frequency in the same time period, undermining the variation. We acknowledge that this restriction likely excludes larger firms that are more active in the market.

[8]Szerman (2012) studies theoretically an auction model considering these features. The model generates two types of equilibria. In one, all bidders bid up to their true valuations before the random phase starts. In this equilibrium, firms do not bid during the random phase (and, therefore, would not be defined as a

auction reaches the random phase, participants are not able to anticipate when it is about to end. Additionally, there is no automatic bidding in ComprasNet so it takes any participant a few seconds to react to a new bid placed by a competitor. See Figure 1 for example: it is clear that the second lowest bidder was about to place a new, incrementally lower new bid had it had a few more seconds. Additionally, had the auction ended a few seconds earlier, the result would have been reversed. For these reasons, as long as participants are outbidding one another frequently the identity of the lowest bidder is as good as randomly assigned (Appendix Table A3 shows exactly that: the average close auction's random phase lasts just under 15 minutes, but it has more than 46 outbids).

4.1 Validating the Empirical Design

In this section, we provide preliminary evidence that validates our empirical design. Table 1 compares winners and runners-up in the close auctions we use in our analysis. All outcomes are measured in the year before the auction. Firms are identical in our main outcome: the difference in annual average wages is 7 *Reais* (around 1.4 dollars), and not statistically significant. Furthermore, there are no significant differences between the winner and runner-up with respect to the number of employees or worker composition. The share of female employees, employees with college, high-skilled, low-skilled, and management occupations are similar. Finally, the difference in firm age between winner and runner-up is only of 4.08 months. These patterns reinforce the intuition that winner and runner-up are as good as randomly assigned in our design.

4.2 Empirical Estimation

Our goal is to test whether a firm-specific demand shock affects wages and employment of competing firms in the same labor market. We test this by comparing the lowest bidders and runners-up in close auctions, as defined above. For each competitive auction, we first keep only the lowest bidders and runners-up and discard all other firms in the auction. Then, we identify all firms in the local labor market of each lowest bidder. These firms are our treatment group. As our control group, we consider all firms in the local labor market of

close auction in our design), and the winner is the one with the highest valuation. The other equilibrium is where firms outbid each other by tiny amounts, trading off the probability of winning for a better selling price conditional on winning.

Table 1: Balancing: Winner *versus* Runner-up

	Means		Difference
Variables at Year$_{t-1}$	Runner-up	Winner	Runner-up vs Winner
(Annual average) Wage (2018 R$)	1186	1194	7
	(692)	(746)	(8)
Contractual Wage (2018 R$)	1139	1148	9
	(618)	(618)	(7)
Employees	14.2	13.3	-0.9
	(163.1)	(132.3)	(0.9)
Firm age (years)	9.07	8.73	-0.34***
	(7.85)	(7.80)	(.11)
% College	15.7	16.2	0.5
	(26.4)	(26.9)	(0.4)
% High Skill	5.0	5.0	0.0
	(15.6)	(15.6)	(0.2)
% Intermediate Skill	6.1	6.1	-0.05
	(16.4)	(16.3)	(0.2)
% Low Skill	81.6	81.4	-0.3
	(27.3)	(27.6)	(0.4)
% Female	41.3	41.3	0.1
	(33.8)	(33.9)	(0.5)
Log(quality)	6.73	6.74	0.01
	(0.69)	(0.70)	(0.01)
Observations	105,668	105,668	211,336

Notes: Table shows means and standard deviations of selected pre-determined variables for winners and runners-up of close auctions. Difference is obtained from a regression with auction-fixed effects and standard errors clustered at the firm level. Standard errors are shown in parenthesis. All firm outcomes are measured at the year before the auction. "Log quality" represents predicted log wage based on worker demographics. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

each runner-up. Finally, we compare treated and control firms for each auction. To do that, we estimate the following reduced-form specification:

$$Y_{iat} = \beta_0 + \beta_1 \mathit{Lowest\ Bidder}_{ia} + \theta_a + \delta' X_{ia} + u_{iat} \tag{28}$$

Our main outcome Y_{iat} is the outcome of interest (wage or employment) of a firm i, that is in the same labor market of a participant in an auction a. We run this specification separately for $t = 0, 1, 2$ years after the auction. *Lowest Bidder* is a dummy with value equal to 1 if the firm is in the local labor market of the lowest bidder at the (random) end of the auction (equal to 0, for those in the labor market of the runner-up). We add auction fixed-effects, θ_a, since the quasi-randomization is at the auction-level. Finally, X_{ia} are potential additional firm-specific controls. In general, we control for the firm size of the auction participant, and firm size and wage of the competing firm (all measured at the year before the auction). When a firm can participate in more than one labor market (for instance, for occupation-based definitions of local labor markets), i refers to a firm-labor market pair.

4.3 Local Labor Market Definitions

An important step for our analysis is the definition of a local labor market. The literature on labor market concentration has considered many different definitions, commuting zone-industry-occupation (Azkarate-Askasua and Zerecero, 2023), county-occupation-time (Guanziroli, 2022; Azar et al., 2020, 2022; Marinescu et al., 2021), microregion-occupation pairs (Felix, 2021), county-industry-year (Benmelech et al., 2022), and commuting zone-industry (3-digit) pairs (Berger et al., 2022). In this paper, we define local labor markets as a municipality-industry-year combination and also consider muncipality-occupation-year combinations.[9]

5 Results

5.1 Employment and Wage Effects on Auction Winners

The theoretical frameworks in Section 2 have shown how changes in wage and employment of a firm can impact wages and employment of other firms in the market. To analyze the response of competitors, we must first verify whether winning an auction impacts the size and the wages paid by the winning firm. Once this is verified, we can proceed with analyzing the potential effects on other firms from the same market.

Therefore, we start by considering a sample with firms that are either the lowest bidder or runner-up only. The results reported in this subsection come mostly from Carvalho et al. (2023). Table 2 shows the effect of being the lowest bidder on firm size (Columns (1) to (3)).[10] We find that being the lowest bidder causes the firm to have 1.7%-2% more employees on average up to two years after the auction.

Next, we estimate the effects on firm wages (Columns (4) to (6)). As shown in Columns (1)-(3), wages in the lowest bidder firm are 0.9% higher compared to runners-up by the end of the year of the auction. After one year, auction winners pay 1.3% higher wages.

[9] Municipalities in our data are closest to counties in the United States.

[10] The number of observations varies across our estimations for two main reasons. First, it is due to the overlap between our auction data (2011-2016) and RAIS (2009-2017). We are not able to follow firms for long periods for more recent auctions. For instance, to estimate the wage effects 2 years later, we can only use auctions conducted in 2015 or before. Second, firms may not be observed in future years in the data (firm survival or attrition). Together, these factors make our number of observations drop substantially across the years of analysis.

Results persist even two years later when wages are still 1.6% higher. All of these estimates are statistically significant.

Table 2: Effects on Auction Participants

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	0.0181***	0.0195***	0.0176***	0.00872**	0.0133***	0.0158***
	(0.00435)	(0.00486)	(0.00589)	(0.00345)	(0.00356)	(0.00382)
Auction FEs	✓	✓	✓	✓	✓	✓
Observations	511,842	500,164	421,296	254,794	247,980	190,570

Notes: Regressions of log number of employees and log wages $j = \{1, 2, 3\}$ years after the auction on the lowest bidder. Unit of observation is an auction-firm. Regressions are run separately for each j. *Lowest bidder* is a dummy taking value 1 if the firm was the lowest bidder and 0 if the firm was the runner-up. Regressions only include lowest bidder and runner-up firms of close auctions. All regressions include auction fixed effects. Standard errors are clustered at the firm level. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

Winning a competitive auction is not necessarily a meaningful demand shock for every firm. The demand shock is possibly more substantial for younger firms.[11] Motivated by this, we run our analysis, splitting the sample between young (age less or equal to 8 years) and old (9 years or older) firms. We do observe a significant effect on firm size for both young and old firms. Young firms have a strong response in the short run (year of the auction), while old firms present larger effects in the long run (Appendix Table A4).

The effect of winning an auction on wages is stronger for young firms. The reduced-form estimates (Appendix Table A4) show that being the lowest bidder causes a significant effect on wages one year after the auction. This effect is amplified in the second year. On the other hand, our point estimates for older firms are economically small and not statistically significant.

These results are consistent with recent evidence that winning a procurement contract affects firm growth, especially among young firms. The impact on young firms is likely due to building reputation, learning-by-doing, and the overcoming of financial and demand constraints (Ferraz et al., 2021; Lee, 2021; Giovanni et al., 2024). Importantly, regardless of the mechanisms driving firm growth and higher wages, our main object of interest is how competitors react as a result.

[11] Ferraz et al. (2015) show that procurement demand shocks are mostly relevant for young firms.

5.2 Employment and Wage Effects on Other (Competing) Firms

Having established that winning a close auction leads to higher wages and size, we now want to estimate our main object of interest: how other firms in the same labor market (competitors) react as a result. We start by considering the local labor market as a municipality-industry-year cell.

Table 3 shows the effect of being in the same local labor market of the lowest bidder on firm size (Columns (1)-(3)) and firm-level wages (Columns (4)-(6)) relative to being in the same local labor market as the runner-up. We find that being in the same local labor market as the lowest bidder causes firms to have 0.2% more employees on average at the year of the auction, an effect that is significant at the 1% level. The effect is no longer significant one and two years after the auction, decreasing to a magnitude of 0.1%. Next, looking at the effect on firm wages, we find that being in the same local labor market as the lowest bidder leads to 0.15% higher wages in the year of the auction, an effect that is significant at the 1% level (Columns (4)-(6)). This grows to 0.18% and 0.23% one year and two years later, respectively, while remaining significant at the 1% level. These magnitudes imply that for every 1% increase in wages by the lowest bidder, wages increase by 0.168% for competitors at the moment of the auction, by 0.134% one year later, and by 0.142% two years later.[12]

Table 3: Effects on Competitors

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	0.00206***	-0.00092	0.00161	0.00147***	0.00179***	0.00225***
	(0.00079)	(0.00131)	(0.00149)	(0.00034)	(0.00045)	(0.00058)
Auction FEs	✓	✓	✓	✓	✓	✓
Observations	117,173,535	117,173,535	117,173,535	116,758,333	100,986,251	89,908,530

Notes: Regressions of log of number of employees (columns 1-3) and log of wages (columns 4-6) of competing firms $j = \{0, 1, 2\}$ years after the auction on the lowest bidder of an auction participant in the same labor market. Unit of observation is a firm-auction-participant. The sample includes all firms in the same labor market of the auction lowest bidder and the runner-up. Regressions are run separately for each j. *Lowest bidder* is a dummy taking value 1 if the participant was the lowest bidder and 0 if the participant was the runner-up. All regressions include auction fixed effects. Standard errors are clustered at the participant level. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

We also verify to what extent the effect on wages and the size of competitors depends on the auction participant's age. The effect on size of competitors is imprecisely estimated for both young and old auction participants, becoming significant in the long run only for

[12] These numbers were calculated by dividing the effect found for wages of the lowest bidder (Table 2) by the effect found for wages of competitors (Table 3), $\frac{0.00147}{0.00872}$, $\frac{0.00179}{0.0133}$ and $\frac{0.00225}{0.0158}$.

young auction participants (see Appendix Table A5). The effect on the wages of competitors is present for both young and old auction participants (see Appendix Table A5).

To summarize, being in the same local labor market as a winner of a close auction leads to an increase in wages by competitors with no discernible change in their firm size. A first explanation is that firms strategically compete for workers with each other on the margin of wages. A second possible explanation is that when the lowest bidder grows (after winning a close auction), aggregate labor demand increases in the local labor market, putting upward pressure on wages via general equilibrium effects. Intuitively, we would expect the strategic interaction motive to be stronger when the firm winning the close auction has a larger share of the local labor market. In contrast, general equilibrium effects should imply higher wages for competing firms regardless of the local labor market share of the firm winning a close auction. With this in mind, we now verify to what extent our results differ by the labor market share of the auction participant.

We find a small positive significant effect on firm size of being in the same local labor market as the lowest bidder for below median labor market auction participants but the effect disappears already 1 year later (Table 4, Panel A Columns (1)-(3)). For above median labor market auction participants, we find a small negative effect on firm size of being in the same local labor market as the lowest bidder but this effect disappears 2 years after the auction (Table 4, Panel B Columns (1)-(3)). Next focusing on wages, we find that the effect of being in the same local labor market as the lowest bidder is entirely driven by above median local labor market share participants. More precisely, being in the same local labor market as the lowest bidder when auction participants have high (above median) local labor market shares leads to 0.26% higher wages in the year of the auction, an effect that is significant at 1%. This effect grows to 0.37% and 0.48% one year and two years later, respectively, still significant at the 1% level. Overall, our results are consistent with the interpretation that firms strategically compete with each other via wages.

We have also verified how our estimates vary by the competitor firm's local labor market share. In this case we find no effect on firm size, an effect for wages for both above and below median local labor market share competitors with larger magnitudes for the latter (see Appendix Tables A6, A7 and A8). These findings indicate that the local labor market share of the auction participant plays a larger role in driving our results. For the remainder of the paper, we focus on this source of heterogeneity as opposed to the local labor market share of competitors.

Next, we analyze how our estimates change once we drop from the analysis markets

Table 4: Effects on Competitors by *Auction Participant's* Labor Market Share

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Labor Market Share *Below* the Median			
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	0.00555**	0.00106	0.00651	0.00009	-0.00003	-0.00001.
	(0.00277)	(0.00327)	(0.0000407)	(0.00057)	(0.00074)	(0.00091)
Auction FEs	✓	✓	✓	✓	✓	✓
Observations	57,811,103	57,811,103	57,811,103	57,594,530	49,923,913	44,357,141
			Panel B. Labor Market Share *Above* the Median			
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	0.00130	-0.00374**	0.000865	0.00261***	0.00372***	0.00477***
	(0.00102)	(0.00176)	(0.00125)	(0.000409)	(0.000566)	(0.000734)
Auction FEs	✓	✓	✓	✓	✓	✓
Observations	59,359,486	59,359,486	59,359,486	59,160,866	51,058,826	45,547,813

Notes: Regressions of log of number of employees (columns 1-3) and log of wages (columns 4-6) of competing firms $j = \{0, 1, 2\}$ years after the auction on the lowest bidder of an auction participant in the same labor market. Unit of observation is a firm-auction-participant. The sample includes all firms in the same labor market of the auction lowest bidder and the runner-up. Regressions are run separately for each j. *Lowest bidder* is a dummy taking value 1 if the participant was the lowest bidder and 0 if the participant was the runner-up. All regressions include auction fixed effects. Standard errors are clustered at the participant level. Panel A reports results for below median labor market share lowest bidder and runner-up pairs. Panel B reports results for above median labor market share lowest bidder and runner-up pairs. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

with a very high number of competitors. We focus on markets with less than 500 competitors. Table 5 shows that there is no effect on firm size of being in the same local labor market as the lowest bidder, and the effect on wages goes from 1% at the year of the auction to 2.58% two years later. As shown in Columns (4)-(6) in Table 6, this effect is driven by above-median local labor market share auction participants.

Table 5: Effects on Competitors: Markets with Less than 500 Competitors

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	-0.00164	0.000583	0.00269	0.00099***	0.00197***	0.00258***
	(0.00108)	(0.00165)	(0.00173)	(0.000286)	(0.000381)	(0.000457)
Auction FEs	✓	✓	✓	✓	✓	✓
Observations	16,044,819	16,044,819	16,044,819	15,985,610	13,677,676	12,091,465

Notes: Regressions of log of number of employees (columns 1-3) and log of wages (columns 4-6) of competing firms $j = \{0, 1, 2\}$ years after the auction on the lowest bidder of an auction participant in the same labor market. Unit of observation is a firm-auction-participant. The sample includes all firms in the same labor market of the auction lowest bidder and the runner-up. Regressions are run separately for each j. *Lowest bidder* is a dummy taking value 1 if the participant was the lowest bidder and 0 if the participant was the runner-up. All regressions include auction fixed effects. Standard errors are clustered at the participant level. Table shows results for sample including only markets with less than 500 competitors. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

Table 6: Effects on Competitors by *Auction Participant's* Labor Market Share: Markets with Less Than 500 Competitors

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Labor Market Share *Below* the Median					
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	-0.00659**	-0.000277	0.00173	0.000360	0.00145	0.000622
	(0.00326)	(0.00498)	(0.00367)	(0.000770)	(0.000918)	(0.00116)
Auction FEs	✓	✓	✓	✓	✓	✓
Observations	7,901,383	7,901,383	7,901,383	7,870,938	6,735,691	5,978,175
	Panel B. Labor Market Share *Above* the Median					
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	-0.00111	0.00272	0.00405	0.00143***	0.00259***	0.00432***
	(0.00106)	(0.00192)	(0.00270)	(0.000360)	(0.000529)	(0.000664)
Auction FEs	✓	✓	✓	✓	✓	✓
Observations	8,140,844	8,140,844	8,140,844	8,112,084	6,938,903	6,110,198

Notes: Regressions of log of number of employees (columns 1-3) and log of wages (columns 4-6) of competing firms $j = \{0, 1, 2\}$ years after the auction on the lowest bidder of an auction participant in the same labor market. Unit of observation is a firm-auction-participant. The sample includes all firms in the same labor market of the auction lowest bidder and the runner-up. Regressions are run separately for each j. *Lowest bidder* is a dummy taking value 1 if the participant was the lowest bidder and 0 if the participant was the runner-up. All regressions include auction fixed effects. Standard errors are clustered at the participant level. Table shows results for sample including only markets with less than 500 competitors. Panel A reports results for below median labor market share lowest bidder and runner-up pairs. Panel B reports results for above median labor market share lowest bidder and runner-up pairs. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

While competitors respond to being in the same industry and municipality as the lowest bidder, a natural question to ask is to what extent we observe this for firms competing in the same occupation market. In principle, the reaction of competitors in the same occupation can differ from that of those in the same industry. To the extent that we think of firms reacting only to competitors that are in the same relevant local labor market, this exercise also allows us to ask if occupation should be part of the definition of a local labor market. Next, we then consider the local labor market as occupation-municipality-year cell. Each observation is a firm-occupation unit. Given the high dimension of markets and computational feasibility, we focus on markets with less than 500 firm-occupation observations.

Table 7 shows that, on average, firms do not respond in size or wages to being in the same occupation-municipality as the lowest bidder. However, Table 8 shows this masks substantial heterogeneity. While firms in the same local labor market as a low (below median) labor market share auction participant do not respond, the same is not true for firms in the same local market as a high (above median) labor market share auction participant, which respond in wages (but not firm size). In particular, Column (4)-(6) indicates that firms in the same local labor market as high local labor market auction participants respond with a 0.32%, 0.5%, and 0.48% higher wages at the moment of the auction, one year later, and two years later, respectively. These results suggest that both occupation and industry matter in determining the set of competitors with which firms strategically interact in the labor market.

Table 7: Effects on Competitors: Markets (occupation x municipality) with Less Than 500 Competitors

	(1)	(2)	(3)	(4)	(5)	(6)
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	-0.000472	0.00111	0.000645	0.000566	0.000923	0.000961
	(0.000550)	(0.00100)	(0.00151)	(0.000397)	(0.000613)	(0.000677)
Auction FEs	✓	✓	✓	✓	✓	✓
Observations	39,467,607	39,467,607	39,467,607	39,290,001	33,739,122	28,458,612

Notes: Regressions of log of number of employees (columns 1-3) and log of wages (columns 4-6) of competing firms $j = \{0, 1, 2\}$ years after the auction on the lowest bidder of an auction participant in the same labor market. Unit of observation is a firm-auction-participant. The sample includes all firms in the same labor market of the auction lowest bidder and the runner-up. Regressions are run separately for each j. *Lowest bidder* is a dummy taking value 1 if the participant was the lowest bidder and 0 if the participant was the runner-up. All regressions include auction fixed effects. Standard errors are clustered at the participant level. Markets are defined in this sample as occupation municipality year triplets. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

Table 8: Effects on Competitors by *Auction Participant's* Labor Market Share: Markets (occupation x municipality) with Less Than 500 competitors

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Labor Market Share *Below* the Median					
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	-0.000452	0.000259	-0.000578	-0.000176	-0.000362	-0.000819
	(0.000757)	(0.00121)	(0.00168)	(0.000859)	(0.00126)	(0.00142)
Auction FEs	✓	✓	✓	✓	✓	✓
Observations	14,473,159	14,473,159	14,473,159	14,385,372	11,717,955	9,381,574
	Panel B. Labor Market Share *Above* the Median					
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	-0.00122	0.00233	0.00373	0.00319**	0.00503***	0.00479***
	(0.00144)	(0.00208)	(0.00341)	(0.00129)	(0.00136)	(0.00147)
Auction FEs	✓	✓	✓	✓	✓	✓
Observations	8,260,787	8,260,787	8,260,787	8,224,917	7,073,558	5,922,370

Notes: Regressions of log of number of employees (columns 1-3) and log of wages (columns 4-6) of competing firms $j = \{0, 1, 2\}$ years after the auction on the lowest bidder of an auction participant in the same labor market. Unit of observation is a firm-auction-participant. The sample includes all firms in the same labor market of the auction lowest bidder and the runner-up. Regressions are run separately for each j. *Lowest bidder* is a dummy taking value 1 if the participant was the lowest bidder and 0 if the participant was the runner-up. All regressions include auction fixed effects. Standard errors are clustered at the participant level. Markets are defined in this sample as occupation-municipality-year triplets. Table shows results for sample including only markets with less than 500 competitors. Panel A reports results for below median labor market share lowest bidder and runner-up pairs. Panel B reports results for above median labor market share lowest bidder and runner-up pairs. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

6 Conclusion

In this paper, we tackle an important question: how do firms react to wages and employment set by their competitors? We leverage quasi-experimental variation from procurement auctions where the winning firm sells goods to the government as our sources of firm-specific demand. A unique feature in these auctions generates randomness in the identity of the contract winner: the moment the auction ends is random (chosen by a computer and unknown to participants). Focusing on auctions in which winner and runner-up are constantly outbidding each other incrementally implies winner and runner-up are as good as randomly assigned.

We find that winning one of these close auctions leads to increases in wages and number of employees of the auction winner and higher wages of other (competing) firms in the same local labor market. The effects are driven by competing firms responding to demand shock from firms with high labor market share. Overall, our results are consistent with firms strategically interacting with each other via prices in the labor market (wages). We see our results as directly causally linking a firm's share of the labor market (market concentration) to its strategic behavior (implied by market power).

References

Amodio, F., Brancati, E., Brummund, P., de Roux, N., and Di Maio, M. (2024). Global labor market power.

Amodio, F. and De Roux, N. (2024). Measuring labor market power in developing countries: Evidence from colombian plants. *Journal of Labor Economics*, 42(4):949–977.

Amodio, F., Medina, P., and Morlacco, M. (2022). Labor market power, self-employment, and development. Technical report, IZA Discussion Papers.

Arnold, D. (2019). Mergers and acquisitions, local labor market concentration, and worker outcomes. *Local Labor Market Concentration, and Worker Outcomes (October 27, 2019)*.

Azar, J., Marinescu, I., and Steinbaum, M. (2022). Labor market concentration. *Journal of Human Resources*, 57(S):S167–S199.

Azar, J., Marinescu, I., Steinbaum, M., and Taska, B. (2020). Concentration in us labor markets: Evidence from online vacancy data. *Labour Economics*, 66:101886.

Azkarate-Askasua, M. and Zerecero, M. (2023). Union and firm labor market power. Technical report, Working Paper.

Benmelech, E., Bergman, N. K., and Kim, H. (2022). Strong employers and weak employees: How does employer concentration affect wages? *Journal of Human Resources*, 57(S):S200–S250.

Berger, D., Herkenhoff, K., and Mongey, S. (2022). Labor market power. *American Economic Review*, 112(4):1147–93.

Berger, D. W., Herkenhoff, K. F., Kostøl, A. R., and Mongey, S. (2023). An anatomy of monopsony: Search frictions, amenities and bargaining in concentrated markets. Technical report, National Bureau of Economic Research.

Bhaskar, V., Manning, A., and To, T. (2002). Oligopsony and monopsonistic competition in labor markets. *Journal of Economic Perspectives*, 16(2):155–174.

Cali, M. and Presidente, G. (2023). *Product Market Monopolies and Labor Market Monopsonies*. World Bank.

Carvalho, M., da Fonseca, J. G., and Santarrosa, R. (2023). How are wages determined? a quasi-experimental test of wage determination theories. Technical report, Rimini Centre for Economic Analysis.

Derenoncourt, E. and Weil, D. (2024). Voluntary minimum wages. Technical report, National Bureau of Economic Research.

Dodini, S., Løken, K. V., and Willén, A. (2022). The effect of labor market competition on firms, workers, and communities. *NHH Dept. of Economics Discussion Paper*, (17).

Felix, M. (2021). Trade, labor market concentration, and wages. *Job Market Paper*.

Ferraz, C., Finan, F., and Szerman, D. (2015). Procuring firm growth: the effects of government purchases on firm dynamics. Technical report, National Bureau of Economic Research.

Ferraz, C., Finan, F., and Szerman, D. (2021). Procuring firm growth: the effects of government purchases on firm dynamics. Technical report.

Giovanni, J. D., García-Santana, M., Jeenas, P., Moral Benito, E., and Pijoan Mas, J. (2024). Buy big or buy small? procurement policies, firms' financing and the macroeconomy.

Guanziroli, T. (2022). Does labor market concentration decrease wages? evidence from a retail pharmacy merger.

Jarosch, G., Nimczik, J. S., and Sorkin, I. (2024). Granular search, market structure, and wages. *Review of Economic Studies*, page rdae004.

Lagaras, S. (2019). M&as, employee costs and labor reallocation. *Available at SSRN 3560620*.

Lee, M. (2021). Government purchases and firm growth. *Available at SSRN 3823255*.

Marinescu, I., Ouss, I., and Pape, L.-D. (2021). Wages, hires, and labor market concentration. *Journal of Economic Behavior & Organization*, 184:506–605.

Prager, E. and Schmitt, M. (2021). Employer consolidation and wages: Evidence from hospitals. *American Economic Review*, 111(2):397–427.

Schubert, G., Stansbury, A., and Taska, B. (2024). Employer concentration and outside options. *Available at SSRN 3599454*.

Staiger, D. O., Spetz, J., and Phibbs, C. S. (2010). Is there monopsony in the labor market? evidence from a natural experiment. *Journal of Labor Economics*, 28(2):211–236.

Szerman, D. (2012). *Public procurement auctions in Brazil*. PhD thesis, The London School of Economics and Political Science (LSE).

Thoresson, A. (2021). Employer concentration and wages for specialized workers. Technical report, IFAU-Institute for Evaluation of Labour Market and Education Policy.

Yeh, C., Macaluso, C., and Hershbein, B. (2022). Monopsony in the us labor market. *American Economic Review*, 112(7):2099–2138.

Appendices

Appendix A Proofs

Proof of Proposition 1. We are interested in how the n_{ijt} changes with the size of a competing firm n_{kjt}. Let us take a total derivative with respect to n_{kjt} and n_{ijt}:

$$\alpha\gamma\frac{\partial\frac{y_{ijt}}{n_{ijt}}}{\partial n_{ijt}}dn_{ijt}+\alpha\gamma\frac{\partial\frac{y_{ijt}}{n_{ijt}}}{\partial n_{kjt}}dn_{kjt}=\frac{\partial w_{ijt}}{\partial n_{ijt}}[\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}+1]dn_{ijt}$$
$$+\frac{\partial w_{ijt}}{\partial n_{kjt}}[\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}+1]dn_{kjt}+w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})\frac{\partial(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}}{\partial n_{ijt}}dn_{ijt}+w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})\frac{\partial(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}}{\partial n_{kjt}}dn_{kjt} \quad (29)$$

Using the expression for $\frac{\partial w_{ijt}}{\partial n_{ijt}}$

$$\alpha\gamma\frac{\partial \frac{y_{ijt}}{n_{ijt}}}{\partial n_{ijt}}dn_{ijt} + \alpha\gamma\frac{\partial \frac{y_{ijt}}{n_{ijt}}}{\partial n_{kjt}}dn_{kjt} = (\frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}})[\frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}} + 1]dn_{ijt}$$
$$+\frac{\partial w_{ijt}}{\partial n_{kjt}}[\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}+1]dn_{kjt}+w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})\frac{\partial(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}}{\partial n_{ijt}}dn_{ijt}+w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})\frac{\partial(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}}{\partial n_{kjt}}dn_{kjt} \tag{30}$$

$$\frac{\alpha\gamma}{n_{ijt}}\frac{\partial y_{ijt}}{\partial n_{kjt}}dn_{kjt}-\frac{\partial w_{ijt}}{\partial n_{kjt}}[\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}+1]dn_{kjt}-w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})\frac{\partial(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}}{\partial n_{kjt}}dn_{kjt} = -\alpha\gamma\frac{\partial \frac{y_{ijt}}{n_{ijt}}}{\partial n_{ijt}}dn_{ijt}$$
$$+(\frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}})[\frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}} + 1]dn_{ijt}$$
$$+ w_{ijt}(\frac{1}{\theta} - \frac{1}{\eta})\frac{\partial(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}}{\partial n_{ijt}}dn_{ijt} \tag{31}$$

Now use the fact that

$$\frac{\partial w_{ijt}}{\partial n_{kjt}} = \frac{w_{ijt}}{n_{ijt}}(\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}} > 0 \tag{32}$$

$$\frac{\partial y_{ijt}}{\partial n_{kjt}} = \frac{\partial z_{ijt}(k_{ijt}^{1-\gamma}n_{ijt}^{\gamma})^{\alpha}}{\partial n_{kjt}} = 0, \tag{33}$$

$$\frac{\partial \frac{y_{ijt}}{n_{ijt}}}{\partial n_{ijt}} = \frac{\partial z_{ijt}k_{ijt}^{\alpha(1-\gamma)}n_{ijt}^{\alpha\gamma-1}}{\partial n_{ijt}} = -(1-\alpha\gamma)z_{ijt}k_{ijt}^{\alpha(1-\gamma)}n_{ijt}^{\alpha\gamma-2} < 0, \tag{34}$$

$$\frac{\partial(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}}{\partial n_{ijt}} = (\frac{1+\eta}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1}{\eta}}(\frac{n_t^{1+\frac{1+\eta}{\eta}} - n_{ijt}^{1+\frac{1+\eta}{\eta}}}{n_t^2 n_t^{\frac{1+\eta}{\eta}}}) > 0, \tag{35}$$

and

$$\frac{\partial(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}}{\partial n_{kjt}} = -(\frac{1+\eta}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}(\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}}\frac{1}{n_t} < 0 \tag{36}$$

to get

$$-\frac{w_{ijt}}{n_{ijt}}(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}[\frac{1+\eta}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}]dn_{kjt}+\frac{w_{ijt}}{n_t}(\frac{1}{\theta}-\frac{1}{\eta})(\frac{1+\eta}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}(\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}}dn_{kjt}$$
$$=\alpha\gamma(1-\alpha\gamma)z_{ijt}k_{ijt}^{\alpha(1-\gamma)}n_{ijt}^{\alpha\gamma-2}dn_{ijt}+(\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}})[\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}+1]dn_{ijt}$$
$$+w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})(\frac{1+\eta}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1}{\eta}}(\frac{n_t^{1+\frac{1+\eta}{\eta}}-n_{ijt}^{1+\frac{1+\eta}{\eta}}}{n_t^2 n_t^{\frac{1+\eta}{\eta}}})dn_{ijt} \quad (37)$$

Combining terms gives

$$-w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}\frac{1+\eta}{\eta}[\frac{1}{n_{ijt}}-\frac{1}{n_t}(\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}}]dn_{kjt}-\frac{w_{ijt}}{n_{ijt}}(\frac{1}{\theta}-\frac{1}{\eta})^2(\frac{n_{ijt}}{n_t})^{\frac{2(1+\eta)}{\eta}}dn_{kjt}$$
$$=\alpha\gamma(1-\alpha\gamma)z_{ijt}k_{ijt}^{\alpha(1-\gamma)}n_{ijt}^{\alpha\gamma-2}dn_{ijt}+(\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}})[\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}+1]dn_{ijt}$$
$$+w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})(\frac{1+\eta}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1}{\eta}}(\frac{n_t^{1+\frac{1+\eta}{\eta}}-n_{ijt}^{1+\frac{1+\eta}{\eta}}}{n_t^2 n_t^{\frac{1+\eta}{\eta}}})dn_{ijt} \quad (38)$$

Then it follows that

$$\frac{dn_{ijt}}{dn_{kjt}}=\frac{-w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}\frac{1+\eta}{\eta}[\frac{1}{n_{ijt}}-\frac{1}{n_t}(\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}}]-\frac{w_{ijt}}{n_{ijt}}(\frac{1}{\theta}-\frac{1}{\eta})^2(\frac{n_{ijt}}{n_t})^{\frac{2(1+\eta)}{\eta}}}{\alpha\gamma(1-\alpha\gamma)z_{ijt}k_{ijt}^{\alpha(1-\gamma)}n_{ijt}^{\alpha\gamma-2}+B(B+1)+w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})(\frac{1+\eta}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1}{\eta}}A}<0 \quad (39)$$

where

$$B\equiv(\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}})>0. \quad (40)$$

and

$$A=(\frac{n_t^{1+\frac{1+\eta}{\eta}}-n_{ijt}^{1+\frac{1+\eta}{\eta}}}{n_t^2 n_t^{\frac{1+\eta}{\eta}}})>0. \quad (41)$$

The sign of the derivative comes from the fact that

$$\eta>\theta\Rightarrow\frac{1}{\theta}-\frac{1}{\eta}>0 \quad (42)$$

and by definition since $n_t>n_{ijt}$, $n_t>n_{kjt}$ for all j,k, then,

$$\frac{1}{n_{ijt}}-\frac{1}{n_t}(\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}}>0. \quad (43)$$

It follows that employment of a firm j unambiguously decreases with employment of a competing firm k. Some properties of this response

1. For firms with very low labor market share $\frac{n_{ijt}}{n_t} \approx 0$ we get $\frac{dn_{ijt}}{dn_{kjt}} \approx 0$.

2. When the firm k receiving the shock has a higher labor market share, high $\frac{n_{kjt}}{n_t}$, the effect is smaller because the magnitude of $\frac{1}{n_{ijt}} - \frac{1}{n_t}(\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}}$ decreases.

□

Proof of Proposition 2. Taking the derivative of w_{ijt} with respect to n_{kjt}:

$$\frac{dw_{ijt}}{dn_{kjt}} = \frac{\partial w_{ijt}}{\partial n_{ijt}} \frac{dn_{ijt}}{dn_{kjt}} + \frac{\partial w_{ijt}}{\partial n_{jt}} \frac{\partial n_{jt}}{\partial n_{ijt}} \frac{dn_{ijt}}{dn_{kjt}} + \frac{\partial w_{ijt}}{\partial n_{jt}} \frac{\partial n_{jt}}{\partial n_{kjt}} \tag{44}$$

Now note that

$$\frac{\partial w_{ijt}}{\partial n_{jt}} = (\frac{1}{\theta} - \frac{1}{\eta})\frac{w_{ijt}}{N_t} > 0, \tag{45}$$

$$\frac{\partial w_{ijt}}{\partial n_{ijt}} = \frac{1}{\eta}\frac{w_{ijt}}{n_{ijt}} > 0, \tag{46}$$

and

$$\frac{\partial n_{jt}}{\partial n_{kjt}} = (\frac{n_{jt}}{n_{jt}^{\frac{\eta+1}{\eta}}})n_{kjt}^{\frac{1}{\eta}} = (\frac{n_{kjt}}{n_{jt}})^{\frac{1}{\eta}}, \forall k, \tag{47}$$

and so,

$$\frac{dw_{ijt}}{dn_{kjt}} = \frac{1}{\eta}\frac{w_{ijt}}{n_{ijt}}\frac{dn_{ijt}}{dn_{kjt}} + (\frac{1}{\theta} - \frac{1}{\eta})\frac{w_{ijt}}{N_t}[\frac{dn_{ijt}}{dn_{kjt}}(\frac{n_{ijt}}{n_{jt}})^{\frac{1}{\eta}} + (\frac{n_{kjt}}{n_{jt}})^{\frac{1}{\eta}}]. \tag{48}$$

Now taking the limit of $\frac{dw_{ijt}}{dn_{kjt}}$ for $(\frac{n_{kjt}}{n_{jt}}) \to 0$ we obtain

$$\lim_{(\frac{n_{kjt}}{n_{jt}}) \to 0} \frac{dw_{ijt}}{dn_{kjt}} < 0. \tag{49}$$

From the above expression we see that if

$$\frac{dn_{ijt}}{dn_{kjt}}(\frac{n_{ijt}}{n_{jt}})^{\frac{1}{\eta}} + (\frac{n_{kjt}}{n_{jt}})^{\frac{1}{\eta}} < 0 \Rightarrow -\frac{dn_{ijt}}{dn_{kjt}} > (\frac{n_{kjt}}{n_{ijt}})^{\frac{1}{\eta}}. \tag{50}$$

then $\frac{dw_{ijt}}{dn_{kjt}} < 0$. In other words, if the response in employment of a competitor i, n_{ijt}, to increases in n_{kjt} of firm k is larger than the relative employment of firm k to i, wages of the competitor i decrease. We also see when the firm receiving the shock has a very small labor share, $\frac{n_{kjt}}{n_{jt}} \approx 0$, then, the last term is close to zero and the derivative is negative. □

Proof of Proposition 3. To start let us explicitly state the value functions for a filled and unfilled vacancy. The value function for a filled vacancy is given by

$$rJ_i = y_i - w_i + \delta(V_i - J_i) \tag{51}$$

where y_i is the amount produced by one worker in firm i. Let c_i denote the cost of posting a vacancy for a firm i and q the probability of a firm finding a worker, then,

$$rV_i = -c_i + q(J_i - V_i). \tag{52}$$

Let us start by deriving the explicit expression for the wage paid by a firm i. The first step is to find an expression for $U_i - U$.

Note that

$$rU_i = b + \lambda \sum_j f_j W_j - U_i \lambda \sum_{j \neq i} f_j - \lambda f_i W_i \tag{53}$$

Next, subtracting rU from this expression we get

$$r(U_i - U) = -\lambda(U_i \sum_{j \neq i} f_j - U) - \lambda f_i W_i = -\lambda(U_i(1 - f_i) - U) - \lambda f_i W_i \tag{54}$$

$$U_i - U = -\frac{\lambda f_i (W_i - U_i)}{r + \lambda} \tag{55}$$

Now using the bargaining condition we can rewrite this as

$$U_i - U = -\frac{\lambda \beta (J_i - V_i)}{(1 - \beta)(r + \lambda)} \tag{56}$$

Now using the free entry condition $V_i = 0$, we get

$$J_i - V_i = \frac{c_i}{q} \tag{57}$$

then,

$$U_i - U = -\frac{\lambda \beta c_i}{q(1 - \beta)(r + \lambda)} \tag{58}$$

Next, using the expression for W_i

$$W_i = \frac{w_i + \delta U}{r + \delta} \tag{59}$$

and replacing that in the expression for U gives us

$$U = \frac{b(r + \lambda)}{r(r + \delta + \lambda)} + \frac{\lambda \sum_j f_j w_j}{r(r + \delta + \lambda)}. \tag{60}$$

Next, replacing the expression for W_i inside U_i gives us

$$\frac{U_i(r(r+\delta)+(r+\delta)\lambda\sum\limits_{j\neq i} f_j)}{r+\delta} = b + \frac{\lambda\sum\limits_{j\neq i} f_j w_j}{r+\delta} + \frac{\delta U\lambda\sum\limits_{j\neq i} f_j}{r+\delta}. \tag{61}$$

$$U_i = \frac{b}{r+\lambda(1-f_i)} + \frac{\lambda\sum\limits_{j\neq i} f_j w_j}{(r+\delta)(r+\lambda(1-f_i)} + \frac{\delta\lambda(1-f_i)U}{(r+\delta)(r+\lambda(1-f_i)}. \tag{62}$$

Combining the expression for U_i and U

$$U_i = \frac{b}{r+\lambda(1-f_i)} + \frac{\lambda\sum\limits_{j\neq i} f_j w_j}{(r+\delta)(r+\lambda(1-f_i))} + \frac{\delta\lambda(1-f_i)b}{r(r+\delta+\lambda)(r+\lambda(1-f_i))} + \frac{\delta\lambda^2(1-f_i)\sum\limits_{j} f_j w_j}{r(r+\delta)(r+\delta+\lambda)(r+\lambda(1-f_i))}. \tag{63}$$

It follows that the expression for w_i is given by

$$w_i = \beta y_i + r(1-\beta)[\frac{b}{r+\lambda(1-f_i)} + \frac{\lambda\sum\limits_{j\neq i} f_j w_j}{(r+\delta)(r+\lambda(1-f_i))} + \frac{\delta\lambda(1-f_i)b}{r(r+\delta+\lambda)(r+\lambda(1-f_i))} + \frac{\delta\lambda^2(1-f_i)\sum\limits_{j} f_j w_j}{r(r+\delta)(r+\delta+\lambda)(r+\lambda(1-f_i))}] + \frac{-\lambda\delta\beta c_i}{q(r+\lambda)} \tag{64}$$

Now taking the derivative with respect to w_j we get

$$\frac{\partial w_i}{\partial w_j} = \frac{\lambda f_j}{(r+\delta)(r+\delta(1-f_i))} + \frac{\delta\lambda^2(1-f_i)f_j}{r(r+\delta)(r+\delta+\lambda)(r+\lambda(1-f_i))} > 0. \tag{65}$$

Taking the derivative of this expression with respect to f_j and f_i completes the proof.

□

Appendix B Tables

Table A1: % Auctions and % Value per Group of Products

Categories	% auctions	% value
Vehicles and parts	4.61%	14.78%
Industrial, commercial and agri equipment	5.42%	6.65%
Safety, cooling, hydraulic, etc. equipment	6.87%	7.27%
Building materials, tools, etc.	11.02%	9.79%
Electric and communication equipment	7.66%	6.09%
Medical and scientific equipment	12.81%	12.86%
Computers, parts, etc.	4.23%	2.13%
Furniture	3.64%	4.71%
Food preparation utensils and equipment	6.16%	4.28%
Office supplies and printed material	7.06%	3.72%
Recreation, sports and musical equipment	2.94%	1.19%
Cleaning supplies, packages	6.86%	4.49%
Personal hygiene and clothing	4.70%	4.70%
Live animals ans agricultural supplies	1.84%	1.56%
Food	4.92%	7.31%
Fuels and minerals	3.18%	4.03%
Misc.	6.06%	4.45%

Notes: The table groups close auctions into product categories and reports the fraction of auctions and the fraction of total value in *Reais* that corresponds to each category.

Table A2: Placebo Identity of Lowest Bidder When Auction Ended x Seconds Earlier

Placebo Lowest Bidder if auction ended...		
	Lowest Bidder	Runner-up
2 seconds earlier	0.83	0.17
6 seconds earlier	0.57	0.40
10 seconds earlier	0.43	0.50
14 seconds earlier	0.40	0.50
18 seconds earlier	0.47	0.41
22 seconds earlier	0.60	0.29
26 seconds earlier	0.63	0.25

Notes: The Column "Lowest Bidder" shows the fraction of lowest bidder firms that would have won the contract if the action ended x seconds earlier. The Column "Runner-up" shows the fraction of runner-up firms that would have won the contract if the auction ended x seconds earlier.

Table A3: Close Auction Summary Statistics

	Mean	Standard Deviation
Reference Value (BRL)	52,992	694,242
Winning Bid (BRL)	28,287	433,888
Auction Duration (min)	51.8	51.3
Random Phase Duration (min)	14.7	8.4
Number of firms who submit initial proposal	9.0	6.3
Number of firms during auction	6.1	4.3
Number of firms during random phase	4.5	2.7
Number of firms during last 30 Seconds	2.3	0.7
% Difference between 2 lowest bids	0.12	0.13
Rank of Lowest Bidder's Initial Proposal	2.1	1.3
Rank of Runner-up's Initial Proposal	2.0	1.2
Number of bids in auction	72.6	52.1
Number of bids in random phase	55.0	45.1
Number of outbids in random phase	46.8	36.9
Lowest Bidder's Outbids During Random Phase	18.6	15.0
Runner-up's Outbids During Random Phase	17.0	14.6
Lowest Bidder's Outbids During Last 30 Seconds	1.3	0.4
Runner-up's Outbids During Last 30 Seconds	1.0	0.3
Lowest Bidder's Seconds as Leader During Last 30 Seconds	10.8	6.4
Runner-up's Seconds as Leader During Last 30 Seconds	9.0	5.8
Observations	225,093	

Notes: This table shows summary statistics for close auctions held by federal purchasing units between 2011 and 2016. We define close auctions as those auctions where i) both the winner and runner-up placed bids in the last 30 seconds of the auction, and ii) the runner-up bid does not exceed the winning bid by more than 0.5%.

Table A4: Effect on Auction Participants: Young vs Old Firms

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Young firms			
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	0.0228***	0.0207***	0.0182**	0.0130***	0.0198***	0.0242***
	(0.00603)	(0.00672)	(0.00795)	(0.00493)	(0.00493)	(0.00488)
Auction FEs	✓	✓	✓	✓	✓	✓
Observations	273,074	267,772	228,336	108,920	107,674	82,716
			Panel B. Old Firms			
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	0.00940	0.0262***	0.0296**	-0.00339	-0.00212	0.00356
	(0.00681)	(0.00790)	(0.0122)	(0.00730)	(0.00765)	(0.00804)
Auction FEs	✓	✓	✓	✓	✓	✓
Observations	44,618	43,280	34,732	36,066	34,186	25,632

Notes: Regressions of log number of employees and log wages $j = \{1, 2, 3\}$ years after the auction on contract winner by firm age. Panel A reports results for young firms, defined as those with 8 years or less of existence. Panel B reports results for firms with age of 9+ years. Unit of observation is an auction-firm. Regressions are run separately for each j. *Lowest bidder* is a dummy taking value 1 if the firm was the lowest bidder and 0 if the firm was the runner-up. Regressions only include lowest bidder and runner-up firms of close auctions. All regressions include auction fixed effects. Standard errors are clustered at the firm level. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

Table A5: Effects on Competitors: Young *versus* Old Auction Participants

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Young Auction Participants					
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	0.00201	-0.00040	0.00563***	0.00120***	0.00111***	0.00157***
	(0.00129)	(0.00237)	(0.00184)	(0.00037)	(0.00050)	(0.00061)
Auction FEs	✓	✓	✓	✓	✓	✓
Observations	79,960,814	79,960,814	79,960,814	79,670,550	68,651,076	61,390,665
	Panel B. Old Auction Participants					
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	0.00187	0.00281	-0.00151	0.00229***	0.00320***	0.00382***
	(0.00156)	(0.00198)	(0.00222)	(0.00082)	(0.00112)	(0.00151)
Auction FEs	✓	✓	✓	✓	✓	✓
Observations	37,209,259	37,209,259	37,209,259	37,084,320	32,331,202	28,513,606

Notes: Regressions of log of number of employees (columns 1-3) and log of wages (columns 4-6) of competing firms $j = \{0, 1, 2\}$ years after the auction on the lowest bidder of an auction participant in the same labor market. Unit of observation is a firm-auction-participant. The sample includes all firms in the same labor market of the auction lowest bidder and the runner-up. Regressions are run separately for each j. *Lowest bidder* is a dummy taking value 1 if the participant was the lowest bidder and 0 if the participant was the runner-up. All regressions include auction fixed effects. Standard errors are clustered at the participant level. Panel A reports results for young participants, defined as those with 8 years or less of existence. Panel B reports results for participants with age of 9+ years. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

Table A6: Effects on Competitors by Labor Market Share

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Labor Market Share *Below* the Median					
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	0.00257	-0.00035	0.00160	0.00084	0.00087***	0.00104
	(0.00146)	(0.00186)	(0.00212)	(0.00078)	(0.00110)	(0.00140)
Auction FEs	✓	✓	✓	✓	✓	✓
Observations	47,071,955	47,071,955	47,071,955	46,852,024	39,286,045	34,278,869
	Panel B. Labor Market Share *Above* the Median					
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	0.00164*	-0.00114	0.00220	0.00124***	0.00160***	0.00216***
	(0.00084)	(0.00128)	(0.00163)	(0.00029)	(0.00038)	(0.00049)
Auction FEs	✓	✓	✓	✓	✓	✓
Observations	70,097,507	70,097,507	70,097,507	69,902,294	61,696,664	55,627,283

Notes: Regressions of log of number of employees (columns 1-3) and log of wages (columns 4-6) of competing firms $j = \{0, 1, 2\}$ years after the auction on the lowest bidder of an auction participant in the same labor market. Unit of observation is a firm-auction-participant. The sample includes all firms in the same labor market of the auction lowest bidder and the runner-up. Regressions are run separately for each j. *Lowest bidder* is a dummy taking value 1 if the participant was the lowest bidder and 0 if the participant was the runner-up. All regressions include auction fixed effects. Standard errors are clustered at the participant level. Panel A reports results for firms with labor market share below the median. Panel B reports results for firms with labor market share above the median. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

Table A7: Effects on Competitors by Competitor's and Auction Participant's Labor Market Share: Number of Employees

	(1)	(2)	(3)	(4)	(5)	(6)
	Competitor: **Low** and Participant: **Low**			Competitor: **Low** and Participant: **High**		
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$
Lowest Bidder	0.00549**	-0.000562	0.00140	-0.000577	-0.00472*	-0.00271
	(0.00178)	(0.00264)	(0.00371)	(0.00129)	(0.00276)	(0.00273)
Observations	29,683,552	29,683,552	29,683,552	17,387,856	17,387,856	17,387,856
	Competitor: **High** and Participant: **Low**			Competitor: **High** and Participant: **High**		
Dep Var	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$	$\log(n)_t$	$\log(n)_{t+1}$	$\log(n)_{t+2}$
Lowest Bidder	0.00660*	0.00261	0.0108**	0.000454	-0.00463***	0.00121
	(0.00338)	(0.00381)	(0.00493)	(0.000912)	(0.00171)	(0.00128)
Observations	28,126,067	28,126,067	28,126,067	41,968,494	41,968,494	41,968,494

Notes: Regressions of log of the number of employees from competing firms $j = \{0, 1, 2\}$ years after the auction on the lowest bidder of an auction participant in the same labor market. Unit of observation is a firm-auction-participant. The sample includes all firms in the same labor market of the auction lowest bidder and the runner-up. Regressions are run separately for each j. *Lowest bidder* is a dummy taking value 1 if the participant was the lowest bidder and 0 if the participant was the runner-up. All regressions include auction fixed effects. Standard errors are clustered at the participant level. Sample is split according to whether the competitor firm and the auction participant have labor market share above (high) or below (low) the median. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

Table A8: Effects on Competitors by Competitor's and Auction Participant's Labor Market Share: Wages

	(1)	(2)	(3)	(4)	(5)	(6)
	Competitor: **Low** and Participant: **Low**			Competitor: **Low** and Participant: **High**		
Dep Var	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	-0.000373	-0.000426	-0.00104	0.00387***	0.00602***	0.00720***
	(0.000906)	(0.00107)	(0.00128)	(0.00108)	(0.00174)	(0.00226)
Observations	29,544,030	24,921,478	21,769,887	17,307,478	14,364,172	12,508,667
	Competitor: **High** and Participant: **Low**			Competitor: **High** and Participant: **High**		
Dep Var	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$	$\log(w)_t$	$\log(w)_{t+1}$	$\log(w)_{t+2}$
Lowest Bidder	0.000114	0.00006	0.000330	0.00226***	0.00329***	0.00429***
	(0.000562)	(0.000755)	(0.000908)	(0.00350)	(0.000475)	(0.000616)
Observations	28,049,078	25,0001,084	22,586,222	41,850,279	36,692,068	33,037,485

Notes: Regressions of log of wages from competing firms $j = \{0, 1, 2\}$ years after the auction on the lowest bidder of an auction participant in the same labor market. Unit of observation is a firm-auction-participant. The sample includes all firms in the same labor market of the auction lowest bidder and the runner-up. Regressions are run separately for each j. *Lowest bidder* is a dummy taking value 1 if the participant was the lowest bidder and 0 if the participant was the runner-up. All regressions include auction fixed effects. Standard errors are clustered at the participant level. Sample is split according to whether the competitor firm and the auction participant have labor market share above (high) or below (low) the median. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.